Broadband Speed and Unemployment Rates: Data and Measurement Issues

April 22, 2019

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Abstract

We examine the effects of broadband speed on county unemployment rates in the U.S. state of Tennessee. We merge the older National Broadband Map dataset and the newer FCC dataset in lengthening our broadband access data over the period 2011-2015. Extending the dataset improves the precision of the estimates. Our panel regressions control for potential selection bias and reverse causality and show that broadband speed matters: unemployment rates are about 0.26 percentage points lower in counties with high speeds compared to counties with low speeds. Ultra-high speed broadband also appears to reduce unemployment rates; however, we are unable to distinguish between the effects of high and ultra-high speed broadband. We document beneficial effects of the early adoption of high speed broadband on unemployment rates. Better quality broadband appears to have a disproportionately greater effect in rural areas.

JEL Classification: E24, O18, J64, C23, D12

Keywords: Broadband speed; unemployment rates; selection bias; endogeneity; rural counties

Introduction

As internet connectivity becomes ubiquitous, attention in the U.S. has shifted from expanding access to the internet towards improving the connections of users. The Federal Communications Commission (FCC) reports that over 92 percent of the U.S. population has access to a fixed broadband connection with download speeds of at least 25 megabits per second (Mbps) (FCC, 2018). However, only one in four U.S. households has access to state-of-the-art technologies such as optical fiber which delivers the fastest symmetrical internet access. The National Broadband Plan specifically addresses the need for speed by stipulating that 100 million households or more should have download speeds of at least 100 Mbps and upload speeds of at least 50 Mbps (Mack, 2014).

Academic research has shown that broadband penetration has important economic impacts. However, Middleton (2013) argues that features other than penetration, such as speed and quality of service are also important determinants of the effects of broadband. Kongaut and Bohlin (2017) point out that academic studies on speed are sparse and suggest the need for micro-level studies to serve as guides for policy-makers since they provide more detail on a specific area. We pick up on this suggestion in attempting to further contribute to our understanding of the effects of broadband speed on local economic outcomes. While others have used national and foreign data sets, we examine the effects of broadband speed on unemployment rates in the U.S. state of Tennessee. Our study is motivated by the fact that a Tennessee city, Chattanooga, was the first city in the Western hemisphere to offer gigabit speed broadband to households and businesses in 2011. This study examines the effects of high speed (defined as 100 Mbps) and ultra-high speed (1,000 Mbps) broadband on county unemployment rates from 2011 to 2016. Our approach circumvents inter-state differences in broadband policy and is the first study, to our knowledge, to merge broadband access data from the National Broadband Map (2011 to 2014) and the FCC (post 2014).

Why is broadband speed important?[1] Presumably, broadband facilitates efficiency, heightens productivity and, likely, fosters innovation. The move from dial-up to broadband internet connectivity has shown positive impacts on productivity, growth, employment and poverty levels (Katz et al. 2010; Czernich et al. 2011; Rohman and Bohlin, 2012; Whitacre et al. 2014b). Middleton (2013) and Mack (2014), however, argued that not merely the presence of broadband but the speeds available are likely to be an important consideration when developing strategic plans to enhance the business climate of locations. Similarly, a former FCC Commissioner emphasized the need for gigabit speeds to encourage U.S. innovation (Genachowski, 2013). One analysis concluded that high-bandwidth applications tend to overwhelm mobile data plans and slow connections. This limits or even cuts off many families from e-commerce, banking, health care and other services (Coren, 2016). Lobo (2015) found that high speed broadband not only had impacts on employment and income in Hamilton county, Tennessee, but also in applications to

[1] To clarify, broadband speed is determined by bandwidth and latency. Bandwidth is the amount of data that can be transferred in a second and is measured in bits per second. It is usually the same as speed when downloading files, but may not always be the same in real time applications (e.g. videoconferencing). Speed is also dependent on (low) latency or delay, i.e. how much time it takes for a packet of information to travel from source to destination. Latency is measured in milliseconds and is a function of the electrical characteristics of the circuit. From a practical standpoint, broadband speed is most often characterized in bits per second, i.e. in terms of bandwidth. Latency, by contrast, is not systematically recorded or reported in the same fashion as bandwidth by the FCC or any other agency. Due to this data limitation, our study uses the terms speed and bandwidth interchangeably.

medicine, banking, education, and in the evolution of an entrepreneurial ecosystem, bearing out the narratives in Koutrompis (2009) and Qiang et al (2009). Other positive effects pertained to disaster recovery services for businesses and benefits stemming from intelligent traffic systems. A major benefit cited in the study stemmed from reduced outage minutes due to weather disruptions which was made possible by smart grid technology. Despite these findings, the effects of broadband speed on the broader economy have been understudied. This is mostly because speed innovations in broadband have emerged in a short time span and consequently, the length of time series data on higher broadband speed access is short. Furthermore, the dearth of adoption/use data has constrained quantitative analysis of the conditions under which broadband has an economic effect.

The FCC defines broadband as, "…high-speed Internet access that is always on and faster than the traditional dial-up access" (FCC, 2014). Over time, our perceptions of what constitutes a "fast" Internet connection have changed.[2] As consumer and business uses of the Internet evolve, and new applications become more deeply embedded into everyday life, higher speeds frequently shift from being a luxury to a requirement for many users. In fact, as broadband access becomes ubiquitous, it becomes expected infrastructure and other factors (such as the quality of that access) become more influential drivers of economic growth. Since broadband serves as an enabler of remote information technology access, its implementation could affect organizational and process changes in local enterprises, and thus could have indirect effects on economic outcomes (International Telecommunication Union, 2012). It is also possible that broadband speed serves as a proxy for other factors, such as agglomeration benefits (Mack, 2014). Holt and Jamison (2009) point out that measuring the economic effects of such an investment is difficult because of the need to isolate the unique effects associated with this infrastructure.[3]

Moreover, it is unclear whether there is a linear relationship between broadband speeds and economic impact. It is conceivable that higher bandwidth may be associated with declining returns to scale, i.e. an inverted-U curve (see e.g. Kongaut and Bohlin, 2017 - Table 9, and Stocker and Whalley, 2016). Yet, anecdotal evidence points to the converse: gigabit broadband will allow the development and deployment of high-value applications which cannot be delivered in any other way, suggesting additional bandwidth carries considerable returns. Atkinson et al. (2009) point to four main areas that benefit from enhanced bandwidth: file transfer, video streaming, real-time communication, and the simultaneous use of multiple applications.

This study focuses on the potential incremental impacts of broadband speed on county unemployment rates. We study 95 counties in the state of Tennessee over the period 2011 to 2016. According to BroadbandNow statistics, Tennessee is the 23rd most connected state in the U.S. with 172 internet providers (the average for the U.S. is 153). The major ISPs in Tennessee are AT&T Internet, CenturyLink, Xfinity from Comcast, Charter Spectrum and EPB (BroadbandNow, 2019).

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[2] For example, in 2000 the Federal government defined broadband as any service with a download speed of 200 kilobits per second (kbps) or faster. In 2010, the FCC redefined "basic" broadband service as a connection with speeds of at least 4 Mbps downstream – 20 times faster than the 2000 definition – and at least one Mbps upstream. The current FCC benchmark for broadband is Internet download speed of 25 Mbps or faster and upload speed of 3 Mbps or faster (BroadbandNow, 2018).

[3] Lobo (2015), for instance, asks in the context of Hamilton county, Tennessee, "..how do we attribute [investments and] jobs to particular features [e.g. broadband] of a location when such answers are not elicited from relocating firms?" (p.13) In his qualitative analysis, Lobo reports that ultra-high speed broadband in the county accounted for at least 2,800 new jobs.

A comparison of current broadband coverage in Tennessee relative to the U.S. as a whole suggests that Tennessee's broadband access appears to be fairly similar to the nationwide averages with respect to wired broadband coverage, average download speed, population access to 25 Mbps, 100 Mbps and gigabit speed service, and underserved population (i.e. those with access to less than 2 wired providers).

We use data on broadband access from the FCC Form 477 and National Broadband Map (NBM) databases and estimate a two-way fixed effects or difference-in-difference model. Our research is similar to some work previously done in this area (Shideler and Badaysan, 2012; Mack, 2014; Lapoint, 2015). However, we add to the literature by examining current levels of high speed and ultra high speed broadband, and by studying the effects of incremental speed levels available in various counties. We merge the older National Broadband Map (NBM) dataset (2011-2014) and the newer FCC dataset (2015 on), identify data and measurement issues involved in this process, and demonstrate the value of lengthening the time series of broadband access on the estimated coefficients. We also examine the benefits of early adoption of fast broadband on unemployment rates. Our empirical specification controls for selection bias and for an aspect of endogeneity, i.e. reverse causality. We use panel data models with county and year fixed effects. We use the lags of the explanatory variables to address possible endogeneity and cluster the standard errors at the county level to address the potential issues related to heteroscedasticity and autocorrelation in the error terms.

We find that high speed broadband has significant effects on county-level unemployment rates; however, we were unable to distinguish between the effects of high and ultra-high speed tiers. We also find measurable benefits to early adoption of high speed broadband. Compared to urban areas, the benefits of better quality broadband are disproportionately greater in rural areas.

The rest of this paper is set out as follows: Section II briefly describes broadband efforts in the state of Tennessee; section III summarizes the relevant literature; section IV describes the methodology and data; section V presents the empirical results, and section VI concludes.

II. Broadband Efforts in Tennessee

Broadband access initiatives in the U.S. have mostly stemmed from Federal, rather than state, efforts. In particular, On March 16, 2010, the Federal Communications Commission (FCC) released "Connecting America: The National Broadband Plan." Mandated by the American Recovery and Reinvestment Act of 2009, the FCC's National Broadband Plan (NBP) is mandated to "seek to ensure that all people of the United States have access to broadband capability." The NBP identified significant gaps in broadband availability and adoption in the United States, and in order to address these gaps and other challenges, the NBP set six specific goals to be achieved by the year 2020 (FCC, 2010). Speeds of 100 Mbps in 100 million homes (popularly referred to as "100 squared") would constitute next-generation broadband in most U.S. households. As a milestone, the FCC set an interim goal of 100 million homes with actual download speeds of 50 Mbps and actual upload speeds of 20 Mbps by 2015. The FCC noted that it was likely that 90% of the country would have access to advertised peak download speeds of more than 50 Mbps by 2013. Regarding broadband adoption, the NBP set an adoption goal of "higher than 90%" by 2020.

Tennessee, like many other states, uses a variety of grant and incentive programs to build out broadband coverage, especially in rural areas. This usually takes the form of giving Connect America Fund (or "CAF") grants to ISPs that promise to provide a certain level of service to an area. The CAF grant pays for construction so the ISP can logistically afford to serve a sparsely populated or otherwise challenging area. This effort is funded by an industry tax that is generally passed on to consumers in broadband bills often as a "regulatory fee" or "universal service fee" BroadbandNow, 2017). Since 2010, Connected Tennessee has been awarded about $4.5 million in federal grants for Tennessee's Broadband Initiative. Other federal incentive programs include Community Connect broadband grants, Rural Broadband Access loans, and the Distance Learning / Telemedicine program – all run by the United States Department of Agriculture's (USDA's) Rural Utilities Service. Kruger (2018) reports that Tennessee was awarded over $240 million across these grants from 2009-2016, accounting for 3.3% of all USDA broadband awards.

In 2005, EPB (formerly, The Electric Power Board), a city-owned utility in Chattanooga, developed a strategic plan to build out a new fiber optic infrastructure in the community to modernize the electric system and provide fiber-to-the-home (FTTH) telephone/internet/TV service to residential and commercial customers. At the time, internet service was provided to the area primarily by BellSouth, AT&T and Comcast. Shortly after receiving approval from Chattanooga's City Council in 2007, EPB made a bond offering of $220 million to fund the build out of fiber optic infrastructure that would support a Smart Grid and provide TV, internet and phone service to residents and businesses in their footprint. In November 2009, in the wake of the recession of 2008-2009, EPB received a federal stimulus matching grant in the amount of $111.6 million from the Department of Energy to expedite the build-out and implementation of the Smart Grid.[4] The first broadband customers were connected in the fall of 2009 and the build out was completed roughly 6 years ahead of schedule. In September 2010, EPB made available residential symmetrical internet connection speeds of up to one gigabit per second - the fastest Internet not merely in the country, but in the entire Western hemisphere (Micheli, 2013). Competitive pressures among ISPs resulted in gigabit internet service costs to customers dropping from about $300 per month in 2010 to $70 per month by 2013 (EPB, 2019). Dubbed the "gig city", Chattanooga has received numerous accolades from global sources and has become a model for publicly-owned fiber deployments in the country.

Neighboring counties would like to have the same service as that provided in EPB's footprint. However, Tennessee House Bill 1045, which proposed to allow counties and municipalities to make use of their infrastructure to provide high-speed Internet access to surrounding cities where only low performance services are available, failed to pass a state senate committee. Tennessee remains one of at least 20 states with anti-municipal broadband state laws (BroadbandNow, 2019).

III. Literature Review

With the advent of broadband services in the 1990s, researchers started to examine the economic impact of such internet connectivity. Much of the early work done in this area focused on the impact of simple internet availability (Katz et al., 2010; Czernich et al., 2011). Important studies such as Crandall et al. (2003), Lehr et al. (2005), and Ford and Koutsky (2006) concluded that

[4] This grant was matched $111.5 million in cash by EPB and the City of Chattanooga, and $3.57 million by EPB's private partners, Alcatel-Lucent, Tantalus, and Medium.

communities with broadband experienced faster job and firm growth than non-broadband communities. Kolko (2010, 2012) added that the positive relationship between broadband expansion and economic growth is even stronger in industries with a greater reliance on information technology and in areas with low population densities. Atasoy (2013) concluded that gaining access to broadband services in a county is associated with approximately a 1.8 percentage point increase in the employment rate, with larger effects in rural and isolated areas. She found that broadband technology is complementary to skilled workers, with larger effects among college-educated workers and in industries and occupations that employ more college-educated workers. The relatively larger impacts on rural areas is also reflected in Whitacre et al. (2014b) who concluded that high levels of broadband adoption in rural areas positively (and potentially, causally) impacted income and employment growth. Jayakar and Park (2013) show a significantly negative relationship between broadband deployment and the unemployment rate at the county level in their cross-sectional specification for the year 2011. However, they fail to uncover a meaningful relationship when they extend their analysis to changes over time, and suggest that more work is needed when additional broadband deployment data becomes available.

Regarding the effects of broadband speed, Kongaut and Bohlin (2017) rightly point out that academic research has been sparse despite the fact that "… broadband speed has started to become more recognized by the authorities and included in the targets of national broadband plans in several countries." (p. 15). The literature in this area has taken the form of studying the effects of broadband speed primarily on output (GDP), firm presence and employment. Kongaut and Bohlin (2017) study the impact of average national download speed (sourced from Ookla) on GDP per capita in a sample of 33 OECD countries. They find robust positive effects of broadband speed on GDP, a result that is stronger for lower-income countries relative to higher-income countries. Rohman and Bohlin (2013) measured the impact of broadband speed on economic growth in 34 OECD countries. They studied a quarterly balanced panel dataset during the period 2008-2010 using a two-stage fixed effects panel model. They found that doubling the broadband speed (from 8.3 to 16.6 Mbps) contributed 0.3% to GDP growth compared with the growth rate in 2008 (the base year). Conversely, Gruber et al. (2014) found in a study of 27 EU countries from 2005-2011 that there is a growth impact from moving away from basic broadband (≤ 0.75 Mbps), but then the incremental speed impact appears to level off, i.e. going from 1 Mbps to 2 Mbps. Most of these studies use speed thresholds that are considerably lower than those currently available in the U.S. – in fact, the FCC finds that 87% of all U.S. Census Blocks have access to 25 Mbps, and 56% have access to 100 Mbps (FCC, 2018b).

Broadband speed effects on firm presence were studied by Mack (2014). She modeled broadband speed as a binary dummy variable that indicates whether a census tract had at least one high-speed provider. A high-speed provider was defined as one that provided broadband at speeds of at least 3 Mbps downstream and 768 Kbps upstream. She found that broadband speed is particularly important for firm presence in rural locations suggesting that broadband speed substitutes for the agglomerative benefits of urban locations and enables firms to carry out operations in rural areas. She found a lack of significance of the broadband speed variable across several sectors predicted to show an effect (such as health care or public administration), possibly because the dummy variable for speed failed to capture specific nuances of broadband quality such as speed tiers. Importantly, the insignificant results for speed could be because the threshold speed limits may not have been high enough (only 3 Mbps) to be a differentiating factor.

Results for broadband speed effects on employment are presented in Hasbi (2017) who shows evidence of a positive relationship between municipalities in France with access to 30 Mbps or higher speed networks and the growth of new companies and entrepreneurship. She also found that such "very high-speed" networks helped reduce the unemployment rate by between 7% to 9%. By contrast, Ford (2018) found no evidence that U.S. counties with 25 Mbps broadband speed as of 2013 outperformed those counties with only 10 Mbps speed in terms of average growth in jobs, personal income and labor earnings over the next two years (i.e. from 2013 to 2015). The study controls for selection bias (or covariate imbalance) using a Coarsened Exact Matching (CEM) technique matched on population, population density, the percentage of adults with a college education, and household size. Notably, he considers effects of incremental speed, but confines the analysis to a single increment of 15 Mbps (i.e. moving from 10 to 25 Mbps). Bai (2017) used a pooled first-differenced regression to report a positive relationship between access to broadband speed and the county-level employment rate for eight states between 2011 and 2014. However, Whitacre et al. (2018) found an econometric error with the study, which nullified this finding. They suggested more work was needed to refine existing models and units of analysis to uncover the relationship between broadband speed and employment.

Other studies of broadband speed include Molnar et al. (2015) who report that single-family homes in census block groups with the ability to upgrade to a one gigabit per second Internet connection have a transaction price that is about 1.8% higher than similar homes in neighborhoods where a 100 Mbps connection is available. Previously, Ahlfeldt et al. (2016) estimated the impact of broadband availability on property prices in the UK during 1995–2010 can add up to 5% to a house price.

On the whole, the broadband literature has begun to shift from analyzing the impact of simple availability to assessing the degree to which faster speeds matter. Early findings on this topic are mixed, with positive results found for employment (Hasbi, 2017) and housing (Molnar et al. 2015; Ahlfeldt et al. 2016). Other results suggest that no such employment effect exists, including Ford's (2018) analysis of U.S. counties and Whitacre et al.'s (2018) failed validation attempt of Bai's (2017) work.

IV. Methodology

How might broadband impact employment levels and unemployment rates? Holt and Jamison (2009) argue that broadband applications can potentially substitute for labor, make the use of labor more efficient and change the way work is done and products are produced. They point out that while it seems reasonable that broadband adoption should improve productivity and economic growth, the effects on job growth could depend on employment and demographic trends. Broadband adoption could decrease frictional and structural unemployment by improving the efficiency of labor, but it may also increase structural unemployment by causing changes in the demand for particular labor skills, at least in the short run. They conclude that, "one of the difficulties learned from studies of the effects of ICT is that impacts evolve, perhaps even going through periods of negative growth, while businesses experiment with applications and reorganize their operations." (p. 580) These trade-offs suggest heterogeneous effects that must be empirically sorted out.

Our empirical strategy involves starting with a simple stratification of counties by high versus low broadband speed; then decomposing high speed broadband into high and ultra-high speed categories. In particular, we estimate panel models with fixed effects of the following form:

$$y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it} \quad (1)$$

$$y_{it} = \beta_0 + BB_{\mathrm{H1},i,t-1}\beta_1 + BB_{\mathrm{H2},i,t-1}\beta_2 + X'_{i,t-1}\gamma + \delta_t + \delta_i + \varepsilon_{it} \quad (2)$$

In (1) and (2), the dependent variable is the unemployment rate in county i at time t. Following Hasbi (2017), the right-hand side variables are lagged one period to control for endogeneity arising from potential reverse causality. Several approaches have been proposed to tackle endogeneity in the broadband literature (see Table 2 in Kongaut and Bohlin, 2017). This lagged explanatory variables approach is a common strategy to handle endogeneity in the social sciences, with many articles in political science, economics, and sociology journals arguing that such an approach alleviates endogeneity (Bellemare et al. 2017).[5] Nonetheless, estimates of (1) and (2) using contemporaneous terms are reported in the appendix. X' is a vector of control variables; δ_t and δ_i account for time and county fixed effects, respectively, and ε_{it} is an error term.

The broadband speed variables of interest are dummy variables that capture the percentage of households in a county with access to particular broadband speeds. We examine two speed categorizations:

<u>Speed Categorization 1 for Model (1)</u>:
Low speed: less than 100 Mbps; High speed: 100 Mbps and higher

<u>Speed Categorization 2 for Model (2)</u>:
Low speed: less than 100 Mbps; High1 speed: 100 Mbps and less than 1000 Mbps; High2 (or Ultra-high) speed: 1000 Mbps and above

In (1), the dummy variable follows speed categorization 1 and is binary so that it takes a value of one if the majority of the population in county i had access to high speed broadband in year t; the omitted category is no/low speed. In (1), the coefficient β_1 captures the effect of high speed broadband relative to low speed broadband.

In (2), we explore additional speed effects by separating speeds of 100 to 1000 Mbps (which we now call High1) and speeds of 1000 Mbps and higher (now called High2). We define two binary dummy variables, BB_{H1} and BB_{H2} in line with speed categorization 2. A county is classified as Low, High1, or High2 based on the speed that the highest percentage of their residents have access to. In this specification, the effect of moving from Low to High1 speed is captured by the coefficient β_1, and the effect of moving from Low to High2 (or ultra-high speed) is captured by the coefficient β_2. The incremental effect of going from High1 to High2 broadband speed is captured by the difference ($\beta_2 - \beta_1$).

[5] Other studies (e.g. Czernich et al, 2011; Atasoy, 2013; Kandilov and Renkow, 2010; Lee et al, 2015) also use a lag structure in examining similar research questions.

Several variables are used to control for factors, other than broadband, that independently affect unemployment rates and mitigate the selection bias discussed in Ford (2018). These include county education levels, household income, population diversity, population density and working age population as a fraction of the total population, all sourced from the U.S. Census Bureau. In particular, we expect that unemployment rates should be lower in counties with more educated people, and a larger working age population. Conversely, unemployment is likely to be positively related to population diversity (i.e. percent of the population that is non-white). The effects of population density on unemployment are less clear: for instance, Oded and Murphy (2003) find a negative effect, but Kolko (2012) finds a positive relationship.

We also examine the effects of broadband speed on rural and urban counties. Using the 2013 Rural-Urban Continuum Codes (RUCC) provided by the U.S. Department of Agriculture, counties classified as "metro" (RUCC codes 1-3) were deemed to be urban, and all others were classified as rural (RUCC codes 4-9). By this classification, there are 42 urban and 53 rural counties in the state of Tennessee.

To estimate differential rural/urban effects, we estimate the following models:

$$y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + D * BB_{H,it-1}\beta_{RH} + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it} \qquad (3)$$

$$y_{it} = \beta_0 + BB_{H1,it-1}\beta_1 + BB_{H2,it-1}\beta_2 + D * BB_{H1,it-1}\beta_{RH} + D * BB_{H2,it-1}\beta_{RU} + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it} \qquad (4)$$

In both (3) and (4), D is a binary dummy variable that takes a value of 1 for rural counties, 0 otherwise. In (3), which stems from (1), β_1 captures the effect of high speed broadband in urban counties, (β_1+β_{RH}) is the effect of high speed broadband in rural counties, and β_{RH} captures the additional effects of high speed broadband in rural counties compared to urban counties. Analogously, in (4), which stems from (2), β_1 and β_2 measure the effects of high speed and ultra-high speed broadband in urban counties; (β_1+β_{RH}) is the effect of high speed access and (β_2+β_{RU}) is the effect of ultra-high speed access in rural counties; β_{RH} and β_{RU} capture the additional effects of high speed and ultra-high speed broadband in rural counties compared to urban counties.

Data

We create a panel dataset of the 95 counties in the state of Tennessee over the period 2011 to 2016. Data on the dependent variable (county unemployment rates) for this model are from the Local Area Unemployment Statistics of the Bureau of Labor Statistics (BLS).

The independent variables of interest in our study are the percent of the population with access to particular broadband speeds (by any wireline or fixed wireless technology, excluding satellite). We use broadband availability rather than adoption data in this study for two reasons. While availability data has limitations as pointed out by Ford (2011) and others, Kolko (2012) points out that adoption rates can be influenced by economic growth more so than availability, thereby exacerbating the endogeneity problem. Importantly, from the perspective of our study, adequate

adoption data does not exist. Currently available adoption data only includes information on speed thresholds for broadband which are very slow in the current environment. [6]

To populate the speed categories used in this analysis, data from various versions of the NBM were used. From 2010-2014, these data were collected by state entities as part of a National Telecommunications and Information Administration (NTIA) effort funded by the American Recovery and Reinvestment Act (ARRA). The mapping entity in each state gathered data from Internet Service Providers (ISPs), including the type of technology used, maximum upload and download speeds offered, and a list of all Census blocks served. During this period, the NTIA summarized this data into an "Analyze Table" listing the percentage of residents in a county with access to various speed thresholds and number of providers. However, this program was discontinued after 2014 when ARRA funding expired. In 2015, the FCC took over the task of gathering broadband data for the country. The FCC does not provide a summary table similar to the NTIA's "Analyze Table"; however, the same data can be constructed using the underlying provider-based information.

Merging NBM and FCC data

To extend the broadband access dataset beyond 2014, annual provider records for Tennessee were compiled, with over 420,000 entries (i.e. one for each census block served by each provider). These were aggregated to a single observation for each census block, after calculating the maximum download speed available. Next, these data were then meshed with all census blocks in the state (over 240,000) and the population of those blocks using 2010 data from the U.S. Census. We then use the maximum speed available to residents of each census block to calculate county-level percentages similar to those presented in the NBM Analyze Table. To verify that our data collection procedure worked appropriately, we successfully replicated the 2014 NBM Analyze Table entries using the underlying census-block level provider data at that time. In Table 1, we provide summary data for two states, Alabama and Tennessee. Our replication of the 2014 Analyze Table produces minor mean errors. Thus, we believe that our calculations for 2015 are an appropriate extension of the NBM data. We note, however, that there are some differences between the two datasets – namely, the NBM data was based on *voluntary* participation by providers (and was gathered by a variety of organizations), while the FCC *requires* providers to file the underlying Form 477. In particular, the NBM data was gathered by the organization *Connected Tennessee*, while the FCC itself gathers the more recent data for all states.[7]

Additionally, the FCC data, unlike the NBM, differentiates between availability for consumers and businesses. In compiling the FCC data, we elected to only include those entries that were

[6] The FCC began collecting adoption data on 10Mbps or faster connections in 2015 via their Form 477 efforts. Prior to that, only slower speeds were considered.

[7] Data from the entity that collected broadband data for TN as part of the NBM includes the following blurb: "The first submission of mapping data under the State Broadband Data and Development grant program represented 77% provider participation in Tennessee. In each subsequent submission, staff was able to increase provider participation in the voluntary program. The final data update, submitted in October 2014, included datasets for 98.82% of the provider community" (Connected Tennessee, 2015).

designated as being available to consumers. This means that if a county was categorized as high speed in 2015, this was due solely to broadband availability for consumers.

We use county access to particular speed levels based on advertised download speeds reported by ISPs. We categorize a county as either low, high or ultra-high speed based on the highest percentage of the population with access to the speed categories defined earlier. Note that implausible access data led us to drop 10 counties (Benton, Fayette, Hancock, Lewis, Macon, Meigs, Morgan, Polk, Scott and Shelby) from the analysis.[8] This resulted in an adjusted sample of 85 counties: 37 urban and 48 rural.

V. Empirical Findings

Summary Statistics

Table 2 shows the percent of county population with access to broadband by speed tier. Panel A shows that the access has varied over the years with a sharp rise in access to 100+ Mbps broadband in 2012, ostensibly because of Federal stimulus funding in the wake of the credit crisis of 2008-2009. Additionally, flexible technologies may have facilitated speedy upgrades (especially in the case of municipal deployments) in the wake of Google's announced Gigabit plans around that time. Some nearby private Incumbent Local Exchange Carriers (or ILEC's) may also then have had pressure to upgrade.[9] In the overall sample (2011-2015), 48% of the population had access to 100 Mbps or higher speed on average. However, some 6% of the population still had no broadband or very low speed (< 3 Mbps) broadband (not shown). Even fewer people (5%) had access to gigabit speed and faster broadband.

In Panel B, we show the distribution of counties by speed tiers based on the population access distribution in Panel A. Note that counties are placed in a speed tier based on the highest percentage of the population that had access to a particular speed.[10] Notably, only six counties had gigabit speed broadband in 2015. As previously noted, in 2011, Hamilton County became the first county in the state (and indeed, in the Western hemisphere) to receive ultra-high speed broadband.

Ford (2018) cautions that counties with higher-speed broadband are unlike those with lower-speed broadband, i.e. selection bias could be serious. In Table 3, we present summary statistics on key socio-economic variables for high and low speed counties. We find that low speed counties are characterized by higher unemployment rates relative to high speed counties. Also, low speed counties have smaller populations and population density, lower household income and a slightly smaller proportion of people with at least a high school diploma. The RUCC score for high speed counties is lower suggesting a greater likelihood of being urban/metro counties relative to low

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[8] In each case, the percentage of population with access to low speed/no broadband was reported as significantly higher than in the previous year, which is likely implausible, suggesting a possible problem.

[9] We are grateful to Mike Render of RVA LLC for this insight.

[10] As an example of how a county was classified, consider Wilson county in 2014: 6% of the population had access to less than 100 Mbps, 86% had access to 100 – 1000 Mbps and 8% had access to 1000+ Mbps speed. The county was placed in the "high" speed tier.

speed counties. These statistics indicate that econometric methods must control for potential selection bias. Our regression models use the controls suggested by Ford.

Early Adoption Effects

Does earlier adoption of high speed broadband make a difference? To answer this question, we examine the average unemployment rates in 2016 for those counties that were classified as high speed in 2011-2015 relative to those that were low speed. Mack and Wentz (2017) note that places served by earlier roll-out of high speed broadband are more likely to receive upgrades, which in turn facilitate the efficient transfer of large volumes of information, the transfer of analytical tools from desktops to online web services, and the intensified use of cloud computing for data storage and retrieval. How does this translate into county employment?

In Table 4, we see that in 2011, only eight counties had high speed (100 Mbps+) access. By 2012, as many as 49 counties had access to high speed. The number of new counties accessing high speed broadband dropped sharply to 7 and 1 in 2013 and 2014. By 2015, the total number of counties with high speed access had risen to 61.

Importantly, the data suggest that high speed counties were characterized by roughly one percent lower unemployment rates in 2016 than low speed counties on average (see UR_L - UR_H). Furthermore, the unemployment differential is greater for counties that adopted high speed earlier. For instance, counties that adopted high speed in 2011 had the largest differential in unemployment rates in 2016 (1.57%) relative to counties with low speed broadband.

The last three columns show the effect of high speed broadband on only counties that newly moved to high speed in a particular year. Here, the differential relative to low speed counties is smaller on average, reflecting the missing effects of early adoption of high speed. For instance, in 2012, counties that newly adopted high speed broadband had 0.66% lower unemployment in 2016 compared to low speed counties (UR_L - UR_{H*}). However, when we add the effects of the eight counties that had already adopted high speed in 2011, the differential widens to 0.86%. The average benefit to early adoption (i.e. the difference between UR_L - UR_H and UR_L - UR_{H*}) from 2011 to 2015 appears to be about 0.16 percentage points (if we exclude the single 2014 data point).

This positive association between broadband speed and labor market outcomes does not indicate causality. In particular, it could simply mean that faster broadband was deployed in the "best" locations first – those that already had low unemployment rates. To explore this issue further, we next present our regression estimates in which we explicitly control for various socio-economic factors that help mitigate potential selection bias and reverse causality.

Regression Results

Estimates of (1) and (2) are in Table 5.[11] Note that the Hausman test rejected a random effects model in favor of a fixed effects model. Our models are estimated with standard errors that are

[11] On the suggestion of a referee, the model is estimated without the household median income variable. Adding the variable to the model does not alter our results.

clustered at the county level to address the potential issues related to heteroscedasticity and autocorrelation in the error terms. Estimates of (1) show that broadband speed matters: counties with fast broadband (i.e. 100 Mbps or higher) have unemployment rates roughly 0.26 percentage points lower than counties with low speed broadband. In model (2), we separate ultra-high speed broadband to examine the incremental effects of broadband speed. We find that compared to low speed broadband, ultra-high speed broadband appears to lower unemployment rates - however, the estimate for ultra-high speed broadband is not statistically significant, perhaps due to the relatively small number of observations in the ultra-high speed category.[12]

Our finding runs contrary to those who have not found broadband access effects on unemployment rates (e.g. Jayakar and Park (2013), Czernich (2014), Whitacre et al. (2014a, 2014b)). This is possibly because access alone is not a sufficient determinant of economic outcomes; broadband quality matters as well. We believe that more data and updated speed levels help clarify the relationship between speed and economic outcomes. Later, in Table 8, we show the sensitivity of our estimates to the sample period.

The education and population density controls are statistically significant. The estimates suggest that a one percentage point increase in the educated population results in a decline in unemployment rates by 0.06 percentage points. Likewise, a 10 percent increase in population density results in an increase of 1.018 percentage points in the unemployment rate.

Relative to the unemployment rate differential reported in Table 4, we find that even after controlling for potential selection bias and other fixed effects, the benefits of high speed broadband are significant, albeit smaller. Moreover, our Table 5 estimates do not uniquely capture the early adoption effects (approximately on the order of 0.16 percentage points on average) which could further enhance the effects of broadband speed on employment as we demonstrate shortly.

Robustness test #1: Pseudo-treatment effects

A concern with estimates using data where low and high speed counties exhibit sharply different features is that the effects of other (possibly missing) variables might be confused for effects due to the treatment (i.e. broadband access). Following Ford (2018), we report a simple test of the "unconfoundedness" or "conditional independence" assumption. We estimate the causal effect of the treatment on an outcome that is determined prior to the availability of the treatment effect, based on the logic that the future cannot determine the past. In the context of our study, we regress lagged values of the unemployment rate on current values of broadband access (i.e. the pseudo-treatment) during our sample period. Our results, available on request, show no effects of the pseudo-treatment on historical unemployment rates, supporting the conditional independence assumption.[13]

Robustness test #2: The broadband speed dummy variable

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[12] Regressions run on all 95 counties produce qualitatively similar results to those reported in this section.

[13] Additionally, we ran this "pseudo-treatment" test with 21 regressions using five-year rolling blocks of unemployment data from 1990 to 2010. We found no cases where the broadband speed coefficient was significant at the one percent level, and two cases where the coefficient was significant at the five percent level.

The dummy variable for county broadband speed is based on the highest percentage of the population that had access to a particular speed. Following Ford (2018), we consider an alternative specification of the dummy variable in re-testing model (1). Here, a county is classified as high-speed if at least 80% of the population had access to 100 Mbps or higher broadband; a county is classified as low-speed if at least 80% of the population had access to less than 100 Mbps broadband, *and* less than 20% of the population had access to 100 Mbps or higher broadband. Our results for model (1) are reported in the Appendix as model (1″). Our sample shrinks from 510 to 190 with this experiment; however, this re-definition of the dummy variable has no material impact on the broadband speed coefficient reported in Table 5.

A Rough Approximation of Jobs Created/Saved

The broadband effects reported in Table 5 can be roughly translated into the annual number of jobs saved/created in each county. To do so, we first characterize counties by their average broadband speed over the sample period by sorting counties by their speed tier score each year (i.e. low=0, high=1, ultra-high=2). We then average a county's score over the period 2011-2015. Counties with average scores of 1.5 or higher were classified as ultra-high speed, those with scores between 0.5 and 1.5 were classified as high speed, and counties with scores less than 0.5 were deemed low speed counties. Accordingly, only one county (Hamilton) was classified as ultra-high speed, 53 were classified as high speed, and 31 were classified as low speed, on average over the sample period.

We would then multiply the appropriate coefficient (β_1 or β_2) from Model 2 in Table 5 with the working age population of that county in 2015 to calculate the annual number of jobs saved/created in that county. However, since β_2 was not statistically significant, we use only the β_1 estimate. As an example, consider Hamilton County, TN, which had an average working age population of 187,992 in 2015. By applying a 0.26 percentage point reduction in the unemployment rate to the working age population, we get an estimate of 489 jobs saved/created each year, or roughly 2,444 jobs over a five-year period. A further adjustment of 0.16 percentage points for early adoption would raise the five-year estimate of jobs created/saved for Hamilton county to 3,948. These computations are directly proportional to the size of the working age population, and therefore largest among the biggest counties (Davidson, Knox, Hamilton and Rutherford).

In Table 6, we see that among all the high speed or ultra-high speed counties, the median incremental jobs created/saved is about 59 per year relative to low speed counties. We also show computations for the top 10 and bottom 10 counties arranged by size of the working age population. We caution that these estimates are based on the assumption that the effects of high speed broadband are evenly distributed among counties belonging to a particular speed category. Clearly, this need not be the case. Counties differ in important ways such as demographics, skill-bias, industry structure, and along the rural/urban continuum. Nonetheless, the findings could be instructive for policy purposes especially if studying the effects of a technology on jobs is paramount.

Rural Effects

In Table 7, we present estimates of (3) and (4) to study the differential effects of broadband speed on rural and urban counties. We find that the broadband interaction terms for rural counties are highly significant with larger coefficients than those observed for the full sample. From the model (4) estimates, it appears that rural counties with high speed broadband (100 Mbps or higher) have roughly 0.38 percentage points lower unemployment rates than high speed urban counties; rural counties with ultra-high speed broadband might benefit even more. In such cases, however, the ultra-high speed variable is estimated with substantial error possibly because the number of rural counties with ultra-high speed broadband is small (i.e. only 3 by 2015), and we caution this is a finding that requires further investigation in a larger dataset. The average effects for urban counties as gauged by the coefficients β_1 and β_2, while indicative, are not statistically significant, suggesting likely offsetting effects of technology on job gains and losses, on average.

This (lack of an) urban effect requires further research. Our results are in contrast to those in Whitacre et al. (2014a), who found a positive relationship between broadband availability and employment levels in urban areas (but not rural ones) in 2011. It may be the case that, by the early 2010s, most urban areas had reasonably fast broadband access. As a consequence, rural areas with faster-speed providers had a competitive advantage in finding employment opportunities for their residents, perhaps in jobs emphasizing telework or real-time interaction with urban firms. A recent review of the literature emphasizes the variety of categories in which broadband could impact rural locations – including entrepreneurship, telehealth, and "big data" opportunities for agriculture (Gallardo et al., 2018).

Model Sensitivity Analysis

In Table 8, we show the sensitivity of our estimates to the sample period and to the definition of rural counties. We examine estimates for the 2012-2015 sample period and compare them to our estimates in this paper for the sample period 2012-2016. To be clear, the lag structure used in this paper means that we effectively use speed access data for the period 2011-2015. The comparison sample in Table 8 uses speed access data for the period 2011-2014. Note that all previous studies (to our knowledge) of U.S. broadband speed effects use some version of the NBM Analyze data, restricting their analysis to speed access data in the window from 2011-2014 (e.g. Lapoint, 2015; Mack, 2014; Ford, 2018). This paper adds more speed access data to the analysis by merging the NBM and FCC datasets as previously explained.

The effects of adding more data to the analysis are clear: the first two columns show that more data sharpens the estimates, i.e. the coefficients are estimated with smaller standard errors. Also, we find that the size of the coefficients typically increases. In the next 4 columns, we show the effects of marginally altering the classification of counties as rural or urban. RUCC A is the definition used in the current paper, i.e. urban counties are RUCC 1-3 and rural counties are RUCC 4-9. RUCC B classifies urban counties as RUCC 1-4 and rural counties as RUCC 5-9. This reclassification moves counties that are adjacent to a metro area and have urban populations over 20,000 (i.e. RUCC code 4) from rural into urban. In the columns titled RUCC A and RUCC B, we show that the results are impervious to marginal changes in the rural/urban continuum; the rural effect remains strong and is more precisely estimated with the longer data set.

VI. Conclusion

We attempt to decipher the incremental effects of broadband speed on county unemployment rates in the U.S. state of Tennessee. We use panel data that captures the percent of the population served by different broadband speeds over the period 2011-2015. Our panel regression results show that high broadband speed matters and results in approximately 0.26 percentage points lower unemployment in counties with high speed compared to counties with low speed broadband; ultra-high speed broadband appears to also reduce unemployment rates but our limited sample of such counties prevents us from generating efficient estimates. Additionally, early adoption of high speed broadband could reduce unemployment rates by an average of 0.16 percentage points per year. The results also show that compared to urban areas, the benefits of better quality broadband are disproportionately greater in rural areas.

From a policy standpoint, our research shows that investments in faster broadband can have significant employment effects, especially in rural areas. Our findings are at odds with claims that "…the definition of "broadband" is typically immaterial to economic outcomes…" (Ford, 2018, p.2). While it may make little difference to move from 10 Mbps to 25 Mbps, it could (and our results suggest that it does) make a significant difference to move to 100 Mbps or higher speeds, a view reflected in Mack (2014). Our results consistently show that access to faster speed results in a decrease of 0.2 – 0.3 percentage points in unemployment, which can be in the 100s of jobs for some counties. We believe many local policymakers would consider these effects to be economically meaningful. Our research shows that it can be valuable to examine larger datasets across longer periods of time using current speed offerings. More work is required, however, in understanding speed effects on employment in urban areas. To this end, we reiterate a recommendation in Mack and Wentz (2017) that in studying broadband effects, it is important to consider how and why broadband is used. Thus, a key need in the study of broadband effects on business, for instance, is collecting usage data so that researchers and policymakers are better able to assess multiple aspects of access and use of broadband internet connections simultaneously.

This research should be considered in the broader context of ongoing enquiries into the effects of broadband quality on economic outcomes. Governments worldwide have adopted measures to support the rapid diffusion of broadband and to reduce digital divides. Perhaps the most controversial issue regarding telecom policy pertains to the role of local governments in providing broadband to smaller communities. To that end, Chattanooga's successful fiber deployment is perhaps a useful model for further study.

We find that high speed broadband has a significant effect on county-level unemployment rates; however, we were unable to distinguish between the effects of high and ultra-high speed tiers. Our empirical specification is linear in parameters; other specifications should be explored to investigate the potentially nonlinear relationship between broadband speed and labor market outcomes. The exact mechanism by which broadband infrastructure adds value to communities remains an open question. Anecdotal evidence and case studies (e.g. Lobo, 2015), for instance, show diverse effects across various facets of community life. To the extent that the impacts of such infrastructure might take years to be fully realized, the search for stable, long-term, and possibly nonlinear effects must continue.

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Table 1. Replicating NBM Data on Population Access to Broadband in 2014

	Alabama Counties [N=67]			Tennessee Counties [N=95]		
Speed Tier	Our Calculation	NBM Analyze Table	Mean Error	Our Calculation	NBM Analyze Table	Mean Error
Low	33	34	-1%	35	35	-1%
High	34	33	+1%	55	55	0%
Ultra-high	0	0	0%	5	5	0%

Notes:
Our calculation is based on NBM Census Block-level data as explained in the text. Mean Error is based on the difference between our calculation of the percent of the population with access to a speed tier relative to the NBM Analyze table. A positive (negative) value indicates that our calculation overestimated (underestimated) the speed tier access across all counties, relative to the NBM Analyze table.

Table 2. Summary of Broadband Access

Panel A. Population Access to Broadband Speed

	< 100 Mbps	100 - 1000 Mbps	≥ 1000 Mbps
Average 2011-2015	52%	43%	5%
2011	86%	13%	1%
2012	51%	48%	1%
2013	43%	50%	7%
2014	43%	50%	8%
2015	36%	55%	9%

Panel B. Classification of Counties by Broadband Speed Categories

Broadband Speed Category for Models 1 and 3 [N=85]

	No/Low Speed < 100 Mbps	High Speed ≥ 100 Mbps
2011	77	8
2012	36	49
2013	29	56
2014	28	57
2015	24	61

Broadband Speed Category for Models 2 and 4 [N=85]

	No/Low Speed < 100 Mbps	High Speed 100 Mbps - 1000 Mbps	Ultra-High Speed ≥ 1000 Mbps
2011	77	7	1
2012	36	48	1
2013	30	52	3
2014	29	51	5
2015	24	55	6
Rural (Non-Metro) Counties [N=48]			
2011	48	0	0
2012	28	20	0
2013	24	23	1
2014	23	24	1
2015	21	24	3

Table 3. Summary Statistics on Dependent and Control Variables

Panel A. Full Sample of 85 Counties

	Obs	Mean	Median	Max	Min	Std. Dev
Unemployment rate (%)	510	7.96	7.85	13.80	3.40	2.18
Population	510	62,632	32,292	667,885	5,094	94,578
Population density	510	140.31	73.94	1346.92	18.90	188.99
Working age population (18 to 64) (%)	510	53.92	52.48	71.88	44.43	4.84
Education: High school or higher (%)	510	80.43	80.40	95.60	65.00	5.13
Median household income ($)	510	41,102	39,414	104,367	26,101	9,390
Population Diversity (% Non-White)	510	11.08	7.70	55.30	0.71	10.15
RUCC (1– most urban; 9 – most rural)	510	4.47	4.00	9.00	1.00	2.65

Panel B. Sub-Samples by Broadband Speed (Mean Values)

	All Counties	Low Speed Counties	High Speed Counties
No. of Observations	510	216	294
Unemployment rate (%)	7.96	9.18	7.07
Population	62,632	29,975	86,626
Population density	140.31	71.47	190.88
Working age population (18 to 64) (%)	53.92	52.96	54.62
Education: High school or higher (%)	80.43	78.10	82.13
Median household income ($)	41,102	37,381	43,836
Population Diversity (% Non-White)	11.08	11.17	11.02
RUCC (1– most urban; 9 – most rural)	4.47	5.76	3.52

Table 4. Early Adoption Effects? Impact of Broadband Speed on 2016 Unemployment Rates

Speed tier in	Low Speed Counties		High Speed Counties		Difference	Counties that newly accessed High Speed		
	N	UR_L (%)	N	UR_H (%)	$UR_L - UR_H$ (%)	N*	UR_{H*} (%)	$UR_L - UR_{H*}$ (%)
2011	77	5.62	8	4.05	1.57	8	4.05	1.57
2012	36	5.97	49	5.11	0.86	41	5.31	0.66
2013	29	6.09	56	5.15	0.93	7	5.49	0.60
2014	28	6.05	57	5.19	0.87	1	7.00	-0.95
2015	24	6.14	61	5.21	0.93	4	5.50	0.64
Average		5.97		4.94	1.03		5.47	0.87[§]

Notes: § excludes the 2014 data point.

Table 5. Effects of Broadband Speed on Unemployment Rates

Models:

(1) $y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

(2) $y_{it} = \beta_0 + BB_{H1,i,t-1}\beta_1 + BB_{H2,i,t-1}\beta_2 + X'_{i,t-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

	Model (1)	**Model (2)**
Speed: High (β_1)	-0.2634**	NA
	(0.1009)	
Speed: High1 (β_1)	NA	-0.2575**
		(0.1006)
Speed: High2 (β_2)	NA	-0.2668
		(0.2428)
Education	-0.0600*	-0.0585*
	(0.0318)	(0.0323)
Working Age Population	0.0580	0.0572
	(0.0921)	(0.0923)
Diversity	0.0052	0.0030
	(0.0559)	(0.0570)
Ln Population Density	10.1579***	10.1772***
	(3.3307)	(3.3361)
N	425	425
Degrees of freedom	331	330
County Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
R^2	0.9679	0.9678

Notes:
***, **, * are significant at 1%, 5% and 10%, respectively. Standard errors (in parentheses) are clustered at the county level to address the potential issues related to heteroscedasticity and autocorrelation in the error terms.
Speed categorization for Model (1): Low: < 100 Mbps; High: ≥ 100 Mbps
Speed categorization for Model (2) and (3): Low: < 100 Mbps; High1: 100 Mbps to 1000 Mbps; High2: ≥ 1000 Mbps

Table 6. The Effect of High Speed Broadband on Jobs Saved/Created

County	Average Speed Tier 2011-2015	Average Speed Category	Working Age Population (2015)	Incremental Annual Jobs Saved / Created Relative to Low Speed Counties
MEDIAN	0.8	High	23,453	59
		Top 10 Counties		
Davidson	1.0	High	392,554	1,010
Knox	0.8	High	245,968	633
Hamilton	2.0	Ultra-high	187,992	489
Rutherford	1.0	High	163,029	420
Montgomery	1.0	High	107,281	276
Williamson	1.0	High	104,576	269
Sumner	1.0	High	90,071	232
Sullivan	1.4	High	78,948	203
Washington	0.6	High	67,641	174
Wilson	0.8	High	65,065	167
		Bottom 10 Counties		
White	1.0	High	13,044	34
Hardin	0.8	High	12,576	32
Grainger	0.8	High	11,732	30
Smith	0.8	High	10,155	26
Union	0.8	High	10,022	26
DeKalb	0.8	High	9,748	25
Johnson	0.8	High	9,603	25
Unicoi	0.6	High	9,223	24
Crockett	1.0	High	7,290	19
Grundy	0.8	High	6,589	17

Notes:
Top 10 and Bottom 10 counties arranged according to size of the working age population. Counties were placed in a speed category based on their average speed tier for the period 2011-2015 as follows: Low: ≤ 0.5; High: > 0.5 and less than 1.5; Ultra-high: ≥ 1.5. MEDIAN refers to the median of all counties classified as high or ultra-high speed counties on average.

Table 7. Effects of Broadband Speed on Unemployment Rates in Rural Counties

Models:

(3): $y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + D * BB_{H,it-1}\beta_{RH} + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

(4): $y_{it} = \beta_0 + BB_{H1,it-1}\beta_1 + BB_{H2,it-1}\beta_2 + D * BB_{H1,it-1}\beta_{RH} + D * BB_{H2,it-1}\beta_{RU} + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

	Model (3)	**Model (4)**
Speed: High (β_1)	-0.0659	NA
	(0.1153)	
Speed: High1 (β_1)	NA	-0.0665
		(0.1126)
Speed: High2 (β_2)	NA	0.0970
		(0.3429)
Rural*High Speed (β_{RH})	-0.3889**	NA
	(0.1567)	
Rural*High1 Speed (β_{RH})	NA	-0.3776**
		(0.1561)
Rural*High2 Speed (β_{RU})	NA	-0.6470
		(0.4229)
Education	-0.0515	-0.0490
	(0.0332)	(0.0335)
Working Age Pop	0.0425	0.0405
	(0.0905)	(0.0910)
Diversity	0.0044	0.0018
	(0.0547)	(0.0561)
Ln Population Density	9.9765***	10.0047***
	(3.2053)	(3.2164)
N	425	425
Degrees of freedom	330	328
County Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
R^2	0.9691	0.9691

Notes:
***, **, * are significant at 1%, 5% and 10%, respectively. Standard errors (in parentheses) are clustered at the county level to address the potential issues related to heteroscedasticity and autocorrelation in the error terms.
Speed categorization for Model (3): Low: < 100 Mbps; High: ≥ 100 Mbps
Speed categorization for Model (4): Low: < 100 Mbps; High1: 100 Mbps to 1000 Mbps; High2: ≥ 1000 Mbps
Urban = RUCC 1-3, Rural = RUCC 4-9

Table 8. Model Sensitivity to Sample Period and Rural/Urban Classification

Models:

(1) $y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

(2) $y_{it} = \beta_0 + BB_{H1,i,t-1}\beta_1 + BB_{H2,i,t-1}\beta_2 + X'_{i,t-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

(3): $y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + D * BB_{H,it-1}\beta_{RH} + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

(4): $y_{it} = \beta_0 + BB_{H1,it-1}\beta_1 + BB_{H2,it-1}\beta_2 + D * BB_{H1,it-1}\beta_{RH} + D * BB_{H2,it-1}\beta_{RU} + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

Sample				RUCC A		RUCC B	
Period	**Coeff.**	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (3)**	**Model (4)**
2011-2015	β_1	-0.2053*	-0.1939	-0.0387	-0.0203	-0.0816	-0.0682
		(0.1255)	(0.1305)	(0.1277)	(0.1319)	(0.1194)	(0.1233)
	β_2		-0.2319		0.1823		0.1541
			(0.3829)		(0.3231)		(0.3231)
	β_{RH}			-0.3194*	-0.2930	-0.3079	-0.2688
				(0.1865)	(0.1891)	(0.2213)	(0.2280)
	β_{RU}				-1.1625***		-1.1356***
					(0.3295)		(0.3296)
2011-2016	β_1	-0.2634**	-0.2575**	-0.1006	-0.0977	-0.1006	-0.0977
		(0.1009)	(0.1007)	(0.1094)	(0.1082)	(0.1094)	(0.1082)
	β_2		-0.2668		0.0940		0.0940
			(0.2428)		(0.2894)		(0.2894)
	β_{RH}			-0.4107**	-0.3899*	-0.4107**	-0.3899*
				(0.1976)	(0.1984)	(0.1976)	(0.1984)
	β_{RU}				-0.8756***		-0.8756***
					(0.3241)		(0.3240)

Notes:
***, **, * are significant at 1%, 5% and 10%, respectively. Standard errors clustered at the county level are reported in parentheses.
RUCC A: Urban = 1-3, Rural = 4-9;
RUCC B: Urban = 1-4, Rural = 5-9

Appendix.

Contemporaneous Effects of Broadband Speed on Unemployment Rates

(1′) $y_{it} = \beta_0 + BB_{H,it}\beta_1 + X'_{it}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

(2′) $y_{it} = \beta_0 + BB_{H1,i,t}\beta_1 + BB_{H2,i,t}\beta_2 + X'_{i,t-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

Effects of Broadband Speed on Unemployment Rates – New Dummy Variable

(1′′) $y_{it} = \beta_0 + BB_{H,it-1}\beta_1 + X'_{it-1}\gamma + \delta_t + \delta_i + \varepsilon_{it}$

	Model (1′)	Model (2′)	Model (1′′)
Speed: High (β_1)	-0.2226*	NA	-0.2678*
	(0.1196)		(0.1546)
Speed: High1 (β_1)	NA	-0.2103*	NA
		(0.1160)	
Speed: High2 (β_2)	NA	-0.1822	NA
		(0.2249)	
Education	-0.0646**	-0.0638**	-0.0669
	(0.0280)	(0.0285)	(0.0420)
Working Age Population	0.0700	0.0711	0.0421
	(0.0702)	(0.0706)	(0.1261)
Diversity	0.0125	0.0120	-0.0442
	(0.0338)	(0.0339)	(0.0878)
Ln Population Density	7.1340**	7.1513**	6.8296*
	(2.8947)	(2.8955)	(3.5909)
N	510	510	190
County Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.9620	0.9620	0.9828

Notes:
***, **, * are significant at 1%, 5% and 10%, respectively. Standard errors (in parentheses) are clustered at the county level to address the potential issues related to heteroscedasticity and autocorrelation in the error terms.
Speed categorization for Model (1′): Low: < 100 Mbps; High: ≥ 100 Mbps
Speed categorization for Model (2′) and (3): Low: < 100 Mbps; High1: 100 Mbps to 1000 Mbps; High2: ≥ 1000 Mbps
In model (1′′): High: ≥ 80% population has access to 100 Mbps or higher; Low: ≥ 80% population has access to less than 100 Mbps AND < 20% has access to 100 Mbps or more